MACHINE LEARNING FOR ESTIMATION OF TREE INVENTORY PARAMETERS USING TERRESTRIAL LASER SCANNING, PHOTOGRAMMETRY AND UAV DATA

Igor Kuznetsov[1], Zhenyu Zhang [1,*] Xiaoye Liu[1] and Nab Raj Subedi[2]
[1]School of Surveying and Built Environment, University of Southern Queensland, Toowoomba, Qld 4350, Australia
[2]School of Surveying and Built Environment, University of Southern Queensland, Springfield, Qld 4300, Australia
[*] Corresponding author: Zhenyu Zhang, zhenyu.zhang@usq.edu.au

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ABSTRACT: Accurate estimation of tree inventory parameters is crucial for promoting sustainable forest management, conserving native forests, and developing precise biomass models. However, traditional methods for measuring these tree parameters are both time-consuming and labour-intensive. Moreover, the results obtained from these traditional methods lack the required accuracy for precision forest management and above-ground biomass modelling. To address these challenges, this study aims to leverage remotely sensed data from various sources, including terrestrial laser scanning (TLS), photogrammetry, and UAV data, and combine them with machine learning techniques to estimate tree parameters more effectively. The research was conducted within the Australian Native Woodland Reserve in southeast Queensland, Australia. The TLS data and photogrammetry data provide detailed information not only from the ground but also from within the canopy, while the UAV data offer a top-down view of the forests. The machine learning methods employed in this study included the random forest method and density-based spatial clustering of applications with noise (DBSCAN) method. By using these techniques, the researchers were able to extract native tree parameters with improved efficiency and accuracy. The results demonstrated the success of integrating TLS, photogrammetry, and UAV data for estimating tree inventory parameters in the Australian Native Woodland Reserve. The study found that TLS point clouds were particularly well-suited for extracting most tree parameters, while terrestrial photogrammetry data proved quite accurate in determining the diameter at breast height (DBH) of trees. The UAV data performed well in estimating height-related parameters of the trees. Overall, the integration of machine learning methods with multiple remote sensing data sources enhanced both the efficiency and accuracy of tree parameter estimation. This research contributes valuable insights that can aid in better forest management and conservation efforts in the future.

1. INTRODUCTION

The accurate determination of tree inventory parameters is a prerequisite for the promotion of sustainable forest management, the conservation of native forests, and the development of precise biomass models (Danson *et al.*, 2007; Korpela *et al.*, 2010; Zhang *et al.*, 2011; Bucksch *et al.*, 2014). Traditionally, tree parameters were assessed using primitive tools like clinometers and callipers, resulting in a notably slow process for obtaining these parameters, as pointed out by Liang et al. (2016). Moreover, Olofsson et al (2014) identified two major limitations associated with the traditional field estimation methods for acquiring tree parameters: firstly, these methods could only measure a small number of trees within sample plots, and secondly, conducting detailed measurements for individual trees was a challenging endeavour. Ghimire et al. (2017) also noted that manual methods exclusively relied on diameter at breast height (DBH) and tree height to calculate basal area and volume in allometric equations, which limited the accuracy of tree parameter estimation. Additionally, traditional methods for measuring these tree parameters are both time-consuming and labour-intensive. Moreover, the results obtained from these traditional methods lack the required accuracy for precision forest management and above-ground biomass modelling. Therefore, it becomes imperative to obtain precise estimations of key tree parameters, encompassing dimensions such as diameter at breast height (DBH), tree height, aboveground biomass density (AGB), tree location, crown measurements (diameter, area, and volume), leaf area index, and tree species, as emphasized by Saarinen et al. (2017). Nevertheless, conventional methods for assessing these parameters not only suffer from accuracy issues but are also time-consuming, as noted by Liang et al. (2016). In response to this challenge, remote sensing offers several effective methodologies for estimating tree parameters, including unmanned aerial vehicle (UAV) photogrammetry, as demonstrated by Iizuka et al. (2020), terrestrial photogrammetry, as detailed by Miller et al. (2015), terrestrial laser scanning (TLS), and UAV laser scanning, as explored by Lin and Herold (2016).

Several factors come into play when considering the accuracy of estimating tree parameters using the TLS and the UAV photogrammetric method. These factors encompass issues like occlusion effects, the distance between the scanner or camera and the tree, the type of scanner employed, the positioning of the scanner, georeferencing accuracy, the chosen scanning mode (single-scan or multi-scan), noise levels, plot conditions, and the choice of software, among others. Moreover, it is worth noting that the photogrammetric method's application in forest inventory is relatively recent. Consequently, there has been limited research in this domain, and researchers have often relied on non-professional equipment, such as handheld cameras and video cameras, to gather plot data. Nevertheless, some notable achievements have emerged in this field, with panoramic image views as demonstrated by Berveglieri et al. (2017) and video recordings as exemplified by Itakura and Hosoi (2018) showing promise for individual tree extraction. However, there is still a lack of comprehensive research on applying the photogrammetric method to assess multiple trees within a single area. Nonetheless, it is evident that the ongoing evolution of these methods will likely lead to one eventually superseding the other, as indicated by Huang et al. (2018). This transition may be facilitated by the integration of machine learning techniques, which could automate various stages of data processing and address some of the challenges associated with these methods.

The integration of machine learning methods for extracting tree parameters is a relatively recent development. Furthermore, there exists a noticeable gap in research that not only applies these methods but also comprehensively addresses the outcomes, particularly in the context of improving efficiency, effectiveness, and accuracy. This gap is particularly evident for unsupervised machine learning techniques, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester *et al.*, 1996). As a result, this study represents one of the pioneering applications of the DBSCAN method for extracting Diameter at Breast Height (DBH). To facilitate this novel approach, a dedicated Python script has been developed for the precise implementation of DBSCAN. The primary focus of this research project is to assess the potential of utilising the TLS, an imaging rover, and UAV data in conjunction with machine learning techniques for the estimation of tree parameters. The specific objectives set forth to achieve this goal are as follows: a) develop methodologies for estimating critical tree parameters by leveraging data obtained from TLS, the imaging rover, and UAV; b) conduct a thorough comparative analysis of results derived from these sources; and c) Undertake a comprehensive assessment and validation of the results.

2. MATERIALS AND METHODS

2.1 Study Area

The study area (27°36’17” S. 151°55’51” E) is within the Australian Native Woodland Reserve (ANWaR) which is a 0.7 ha native plant reserve developed for education, research and conservation at the University of Southern Queensland, Toowoomba campus, Australia (Figure 1). The Reserve consists of over 500 native plant specimens planted in three different representative native woodlands found in southern inland Queensland.

Figure 1. Study location within the Australian Native Woodland Reserve at the University of Southern Queensland, Toowoomba campus, Australia.

2.2 Methods

2.2.1 TLS Data and Processing

The TLS data were collected using FARO Focus 3D Laser Scanner (Figure 2a) at six scan stations. Precise scan station coordinates were determined through Real Time Kinematic (RTK) GNSS surveying, employing a Trimble R10 receiver

(Figure 2b). The TLS data acquired from different scan stations were registered together using FARO Scene software. The registered scanning data were then georeferenced to Map Grid of Australia 2020 (MGA 2020), Zone 56 with the assistance of GNSS positioning data. The height of the scanning data was referenced to Australian Height Datum (AHD). To extract the tree parameters, the point cloud was subsequently normalised, eliminating any terrain-related influence on above-ground measurements (as shown in Figure 3). The tree parameters including the DBH, tree height, crown diameter, crown area and crown volume were calculated using the LiDAR360 software.

Figure 2. (a) The TLS data collection; and (b) RTK GNSS surveying.

Figure 3. Normalised TLS point cloud.

2.2.3 Photogrammetry Data Collection and Processing

Terrestrial photogrammetry data were acquired using Trimble V10 imaging rover which is an integrated camera system that precisely captures 360-degree digital panoramic images for visual documentation and measurement of the surrounding environment. The photogrammetry data acquisition was conducted at 24 stations. The Trimble R10 GNSS receiver was used in the integrated mode with the imaging rover to obtain the coordinates of the photogrammetry stations. The Agisoft Metashape software was used to process the photogrammetric images acquired from the V10 imaging rover to generate point cloud data. Similar to the processing of the TLS data, the DBHs were then computed from the cloud data using the LiDAR360 software.

2.2.4 UAV Data and Tree Parameter Extraction

The UAV data over the study area were collected during the same time as the TLS and photogrammetry data acquisition. The pre-processing of the UAV data was conducted in the Agisoft Metashape software and then exported into the LiDAR360 software for automatic extraction of such tree parameters as tree height, crown diameter, crown area, and Leaf

Area Index (LAI). Combined with the TLS data, the UAV data were also able to calculate the parameter of crown volume. It is difficult to extract the crown volume if using the TLS data alone.

2.2.5 Machine Learning

In this study, we employed both supervised machine learning, specifically the random forest machine learning, and unsupervised machine learning, exemplified by the DBSCAN, for the automated extraction of tree parameters. The overall workflow and the datasets utilised in the study are visually depicted in Figure 4. For both the TLS data and the photogrammetry data, we utilised the random forest method, which employs ensemble learning to amalgamate multiple classifiers for resolving intricate problems. This approach was implemented within the LiDAR360 software to extract the DBHs and tree heights.

DBSCAN, an unsupervised clustering machine learning algorithm was used in this study to extract the DBH values from the TLS data. To facilitate the implementation of this algorithm, a Python script was developed in the Spyder environment (Scientific Python Development Environment). The effective deployment of the DBSCAN algorithm necessitated the careful selection of two key parameters: first, the 'eps,' which defines the neighbourhood around a data point (in other words, it determines whether the distance between two points is equal to or lower than 'eps' to consider them as neighbours); and second, the minimum number of data points required to be within the 'eps' radius for a point to be considered a part of the cluster.

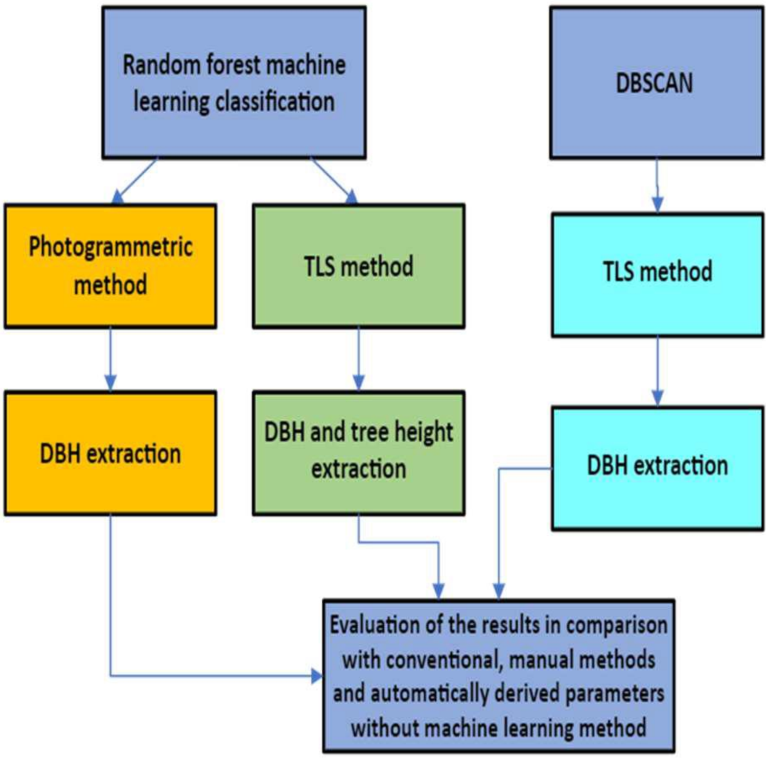

Figure 4. The flowchart showing general procedure of machine learning for tree parameter extraction.

2.2.6 Conventional Measurements for Validation

The circumferences of tree trunks at breast height (around 1.3-1.5 m) for 46 different trees were measured by a steal tape as shown in Figure 5. The DBHs were then calculated for these trees and compared with the DBHs extracted from the TLS and imaging rover data to validate the results. The remote height measurements using a Trible robotic total station were conducted to obtain the tree heights of 30 trees to validated tree heights derived from the TLS and UAV data as described before.

Figure 5. Circumference measurements of tree trunks at breast height.

3. RESULTS AND DISCUSSION

3.1 Results from the TLS Data

Overall, the TLS results demonstrated a high level of tree detection within the study area via segmenting the point cloud for individual trees. Various tree parameters, including DBH, tree height, crown diameter, crown area, and crown volume, were successfully calculated. The automatic classification results from the TLS data were shown in Figure 6. Figure 7 shows segmented trees with estimated DBH values obtained from the TLS data. We achieved a high level of accuracy in estimating DBH in over 90 percent of cases. However, some trees lacked proper overlap between scanning stations, particularly those with small DBH, leading to poor detection. Nevertheless, trees located close to the scanner or with good overlap still exhibited a significantly accurate DBH estimation, even for those with a DBH less than 10 cm.

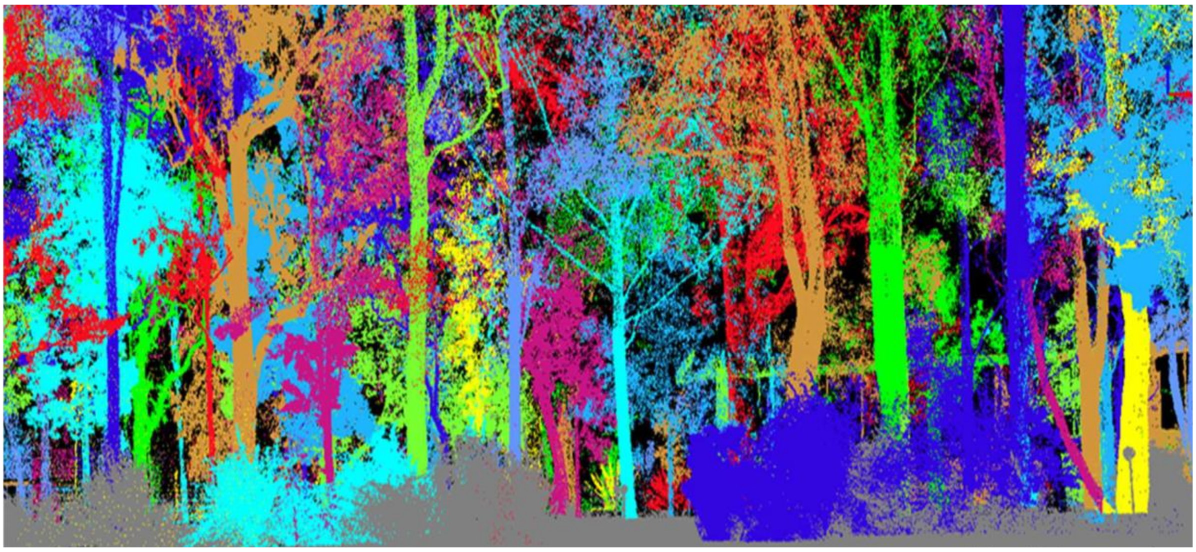

Figure 6. Classification results from the TLS point cloud.

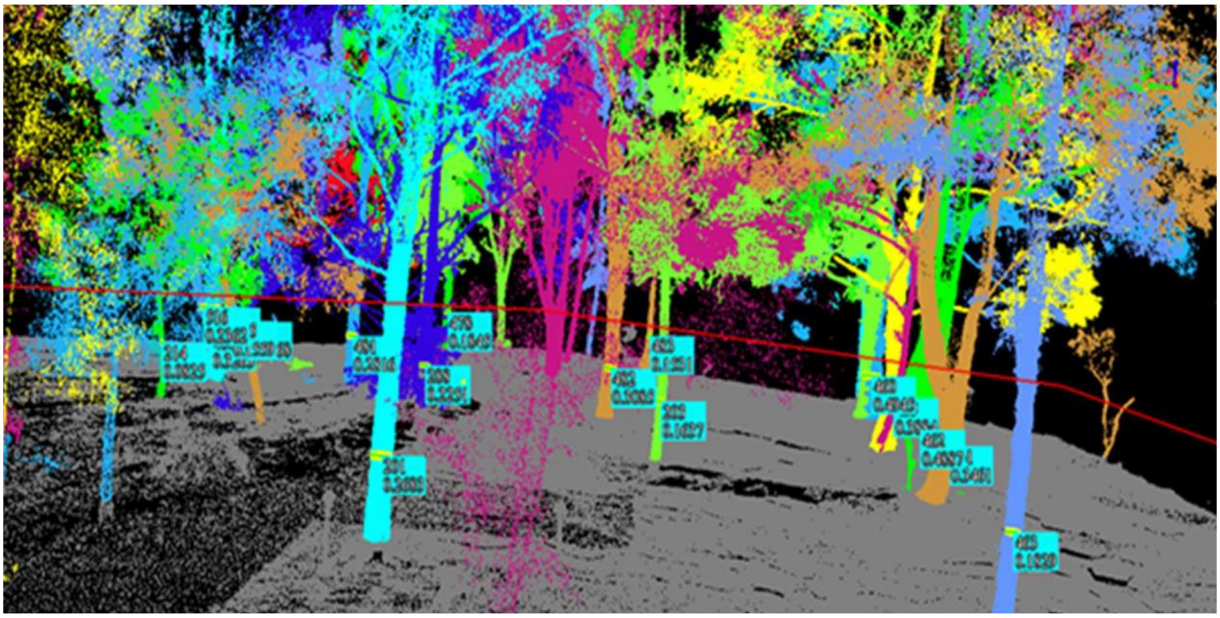

Figure 7. Segmented trees with estimated DBH derived from the TLS data.

3.2 Tree Parameters Estimation from the Photogrammetry Data

The photogrammetric method demonstrated the potential for accurate DBH estimation. Nevertheless, the dense point cloud primarily contained low-quality trunk representations, as there were only a limited number of ground points available for extracting tree parameters. Additionally, the significant noise generated during dense point cloud creation resulted in an unusually time-consuming manual classification of ground points. As a result, the terrestrial photogrammetric method utilising the Trimble V10 imaging rover can be deemed less suitable for tree detection and accurate estimation of tree parameters due to issues with both accuracy and efficiency.

3.3 Contributions from UAV Remote Sensing

UAV remote sensing holds the potential to significantly enhance TLS data for improving estimations of tree height, crown area, crown diameter, crown volume, and LAI. However, challenges arose when TLS results outperformed TLS combined with UAV data due to additional data from UAV causing errors in the segmentation process. This resulted in some parts of the original tree being automatically merged with neighbouring segments, making the neighbouring trees appear larger. In general, TLS combined with UAV data appears to be the optimal data source for accurately estimating not only tree height but also crown diameter, crown area, crown volume, and leaf area index. These parameters heavily rely on tree height and crown data, which can be effectively provided by UAV data.

While TLS results can exhibit good accuracy for tree height when whole trees are observable without occlusion, they tend to suffer from reduced accuracy due to occlusion effects. Consequently, selecting the appropriate segmentation parameters may enhance the detection level for estimating tree height, crown area, crown diameter, crown volume, and leaf area index. However, addressing occlusion effects may necessitate the use of complementary methods, such as UAV remote sensing.

3.4 Machine Learning Results

Following the application of machine learning classification (supervised classification with the Random Forest algorithm) to the TLS point cloud, ground point normalization became feasible, resulting in correct classification for nearly all ground points without the original height distortion (Figure 8). Furthermore, the detection accuracy was high, with ground points reaching 89% accuracy and tree trunks achieving around 60%. It's worth noting that some undetected trunks had structural damage, rendering them unsuitable for DBH estimation, even with manual intervention. Compared to the conventional method, a better classification of both ground points and tree trunks was achieved. The accuracy of DBH extraction was significantly improved.

DBSCAN proves to be an accurate method for DBH estimations using the TLS approach, with minor challenges arising in cases where clusters contain less than half of the points forming a circle or exhibit a broken-spreading structure. For cases involving directly connected double trunks, it's advisable to evaluate them separately using appropriate parameters. Nonetheless, the method remains effective for trees with double trunks as long as they are not directly connected or are separated by a distance greater than or equal to eps. The results revealed that 29 out of 30 trunks were correctly identified.

The DBSCAN method demonstrates its effectiveness in extracting DBH from TLS data, achieving an accuracy of 78.02%, surpassing both the supervised machine learning method in Lidar360 software (76.61%) and the conventional field method.

Figure 8. Classification results from supervised machine learning methods with the Random Forest algorithm.

3.5 Comparison and Validation

Figure 9 shows the DBH values derived from the TLS, Photogrammetry (Trimble V10 imaging rover) data, and conventional measurements. The comparison between TLS and conventional methods revealed differences ranging from -4.0 cm to +2.0 cm. The photogrammetric approach demonstrated potential, with manually detected and processed trunks showing differences from -4.1 cm to +2.1 cm compared to TLS and from -1.3 cm to +1.7 cm compared to conventional methods. However, most trunks were found in the dense, low-quality point cloud, with limited ground points available for parameter extraction. Moreover, the manual classification of ground points was unusually time-consuming due to significant noise generated during the dense point cloud generation process. In general, the TLS results confirmed a high level of tree detection and subsequent DBH extraction.

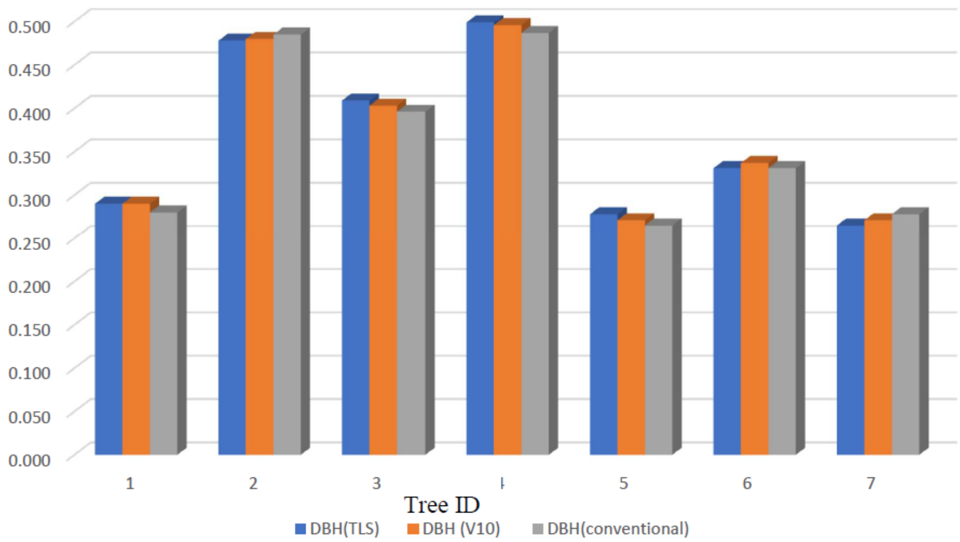

Figure 9. DBH derived from the TLS, Photogrammetry (V10 Imaging Rover) data, and conventional measurements.

4. CONCLUSIONS

Accurate tree inventory parameters play a pivotal role in advancing sustainable forest management, preserving native forests, and refining precise biomass models. This study harnessed remotely sensed data from diverse sources, including terrestrial laser scanning, terrestrial photogrammetry, and UAV data, integrating them with machine learning techniques to estimate tree parameters. The TLS and photogrammetry data not only provide comprehensive ground-level information but also delve into the canopy, while UAV data afford a top-down perspective of the forests. The machine learning methods employed encompassed the random forest method and the DBSCAN. Through these techniques, researchers successfully extracted native tree parameters with heightened efficiency and accuracy. The results underscore the efficacy of integrating TLS, photogrammetry, and UAV data for estimating tree inventory parameters within the Australian Native Woodland Reserve. The TLS point clouds proved particularly adept at extracting most tree parameters, while terrestrial photogrammetry data excelled in determining the DBH of trees. The UAV data performed admirably in estimating height-related parameters. In sum, this integration of machine learning methods with multiple remote sensing data sources substantially enhanced both the efficiency and accuracy of tree parameter estimation. This research contributes invaluable insights that hold the potential to inform more effective forest management and conservation efforts in the future.

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